Resonance, the emergence of meaning and the plausibility of intelligent machines

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The feasibility of intelligent machines

- Limitations of math approximations of real-life phenomena
- Limitations of representing cognition sans biology
- The problem of symbolic knowledge representation (static concepts, dynamic phenomena, multifaceted real-life contexts)
- Robert Rosen's "***<u>nonfractionability of components in an organism</u>***" as the fundamental difference between living systems and machines

Resonance

a. *The math basis of resonance*:

A series of differential equations describe the system dynamics for adaptive resonance.
[ART, Grossberg 1980 et. seq.]

b. *The biological basis of resonance*:

Pollen suggests: “it may be the consensus of neuronal activity across ascending and descending pathways linking multiple cortical areas that in anatomical sequence subserves phenomenal visual experience and object recognition and that may underlie the normal unity of conscious experience.”
[Pollen, D.A., 1999, “On the neural correlates of visual perception”, *Cerebral Cortex*, 9:4-19]

c. *Resonance and attention, categorization, perception*:

“Adaptive resonance offers a core module for the representation of hypothesized processes underlying learning, attention, search, recognition, and prediction. At the model’s field of coding neurons, the continuous stream of information pauses for a moment, holding a fixed activation pattern long enough for memories to change.”
[Gail A. Carpenter, Stephen Grossberg: “Adaptive Resonance Theory”. In *The Handbook of Brain Theory and Neural Networks.* 2002. Michael A. Arbib, Ed., MIT Press]

d. *Resonance in CLARNET*

The stability-plasticity dilemma

The dilemma refers to the problem of preserving learned patterns in a stable state while new patterns are presented to the system.

Resonance and memory

Resonance is independent of memory although it may be facilitated by it.

Pollen (1999) resolves various past and current views of cortical function by postulating ***resonant feedback loops*** as the substrate of phenomenal experience.

"At the model's field of coding neurons, the continuous stream of information pauses for a moment, holding a fixed activation pattern long enough for memories to change. ***Intrafield competitive loops*** fixing the moment are broken by active reset, which flexibly segments the flow of experience according to the demands of perception and environmental feedback." [Carpenter and Grossberg, 2002]

Memory and learning in CLARNET

[Koutsomitopoulou 2004, 2005]

Three scenaria:
1) *STM activation*
-Calculates activation sans LTM
-Not resonant learning
-Learning in a vacuum (without taking into account prior experience - brain doesn't learn like that)
2) *LTM learning sans inhibition of reactive responses*
-Resonant reactive learning
-Learning without conscious decision, choice (intention)
Hypothesis: There's always LTM activation as first reaction to a STM activation/event.
How to prove it: STM activation and LTM learning without inhibition should yield the SAME results
3) *LTM learning with inhibition*
-Resonant responsive learning
-Intented/conscious learning

OR the above can be subsummed in the following two:
1) Learning without inhibition (unsencored LTM-triggered reactive)
2) Learning with inhibition (intended autonomous LTM-censored)

Basic structural unit: Dipole anatomies

Any two adjacent neuronal columns form a ***dipole***. Dipoles can phase-lock into an oscillatory pattern of ***rebounds*** that clock much of human serial behavior. For example, when we walk our left and right hemispheres oscillate as a dipole.

On-center off-surround neocortical anatomies

Neocortical columns excite themselves ("on-center") and inhibit neighboring columns ("off-surround")

=>

contrast-enhancement cognitive phenomena

Neocortical OCOS architecture and hierarchical temporal memory

-The neocortex is capable of making specific predictions from invariant memories.

-In a cortical column, the OCOS architecture means that neurons:

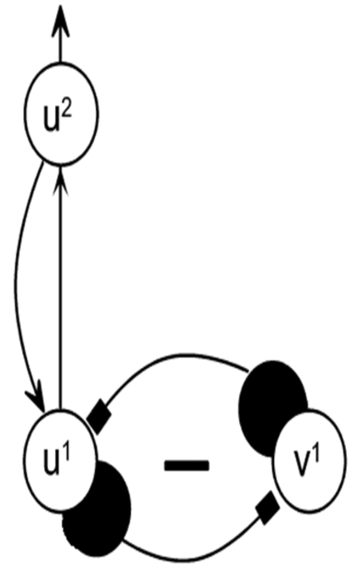
a. excite very close neighbors

b. inhibit neighbors in a wider neighborhood

c. do not affect neurons further away

[figure from Loritz 1999]

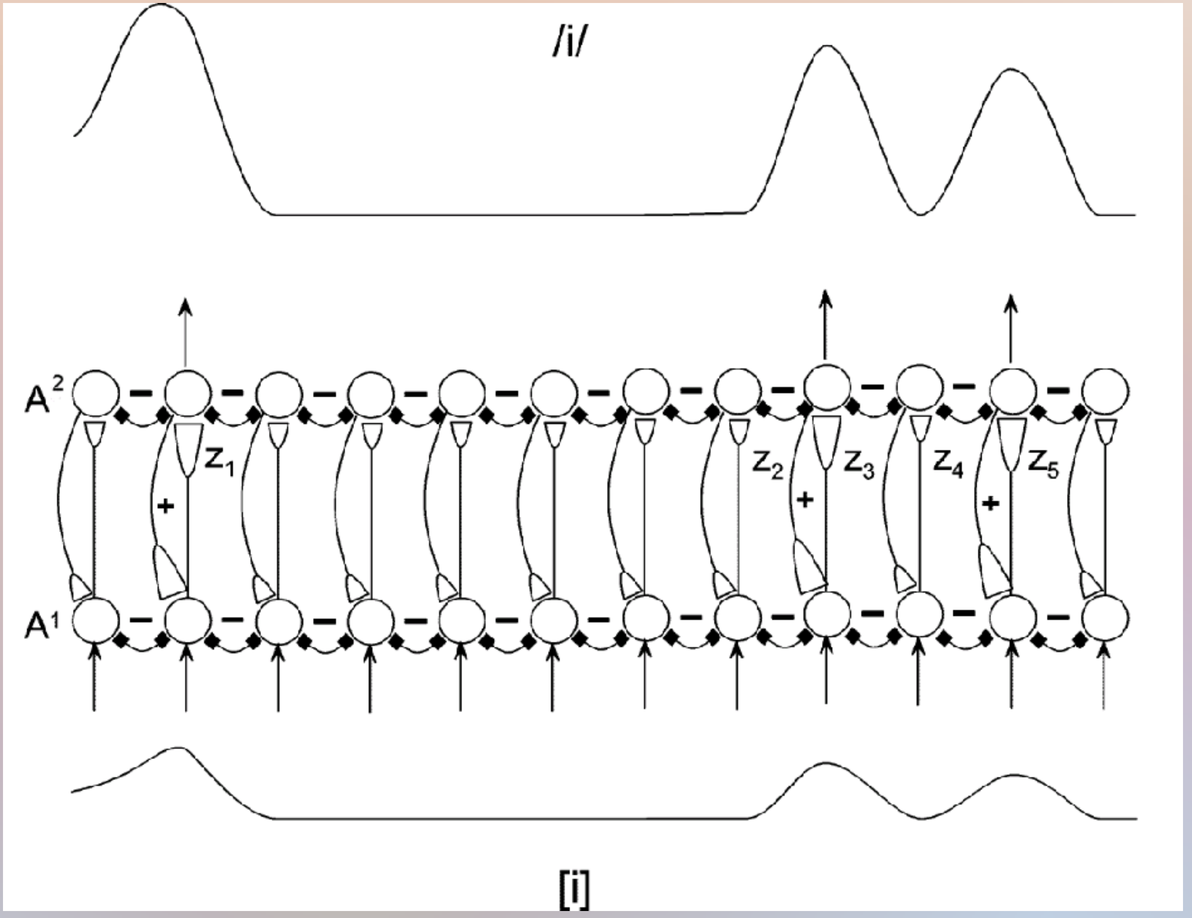
On-centre off-surround anatomies



An example of contrast-enhancement as an effect of OCOS neocortical anatomies

Modelling OCOS phonemicization

The columns at the center of the input formants of [i] excite themselves ("on-center") and inhibit neighboring columns ("off-surround"). The resulting output to A2 is a contrast-enhanced "phoneme" /i/.



[figure from Loritz 1999]

System dynamics

(i) $d/d_t x_j = -A\, x_j + \Sigma_i B\, x_i n_{ij} - \Sigma_k C\, x_k n_{kj}$

(ii) $d/d_t\, z_{ij} = -D\, z_{ij} + E\, x_i\, x_j$

(iii) $d/d_t\, n_{ij} = +F\, z_{ij} - G\, x_i\, n_{ij}$

CLARNET

[Koutsomitopoulou 2004]

a. CLARNET

1. targeted data
2. network architecture
3. numerical results
4. graph analysis

b. Evaluation of CLARNET through:

1. plausibility according to linguistic theory
2. validity via cognitive and neurophysiological hypotheses and related experiments

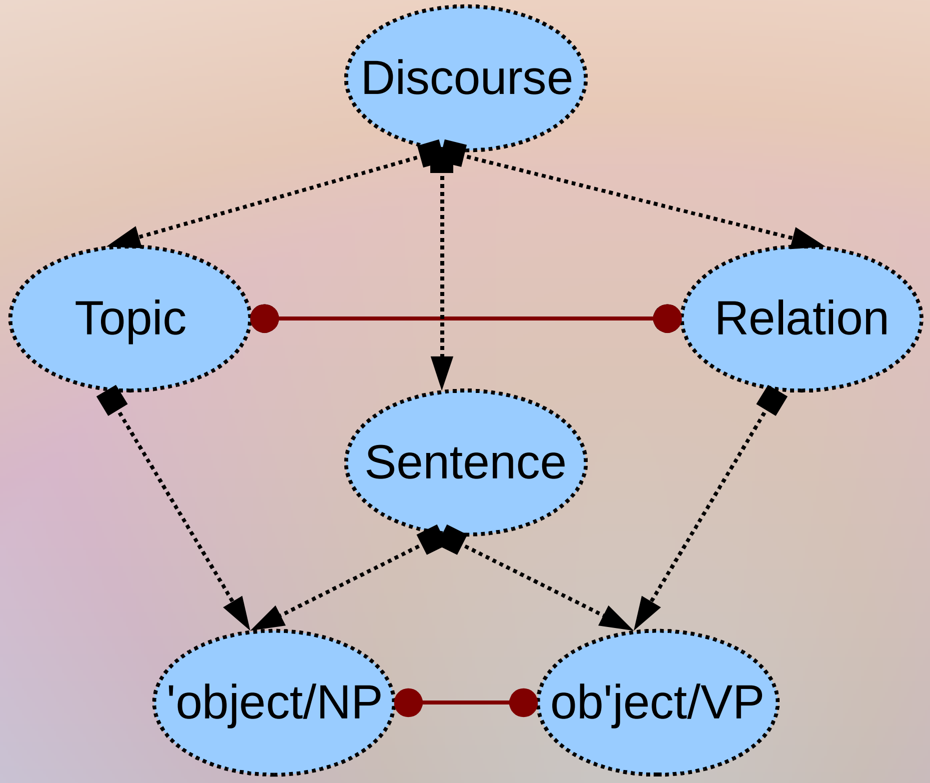
Published applications of the model

- modelling pattern recognition for *word disambiguation*
- modelling of particular instances of linguistic vagueness or underspecification such as:
  - *homonymy,*
  - *neologism,*
  - *polysemy,*
  - *metaphor,*
  - *constructional polysemy,*
  - *contextual coreference,*
  - *subject-object control,*
  - *event-structure metaphor*
  - *negation*

Published applications of the model (cont.)

- modelling for purposes of fact resolution (record linking) in legal databases
- modelling of the generation and usage of inference
- exemplifying basic adaptive grammar tenets in Greek and English
- modelling the process and effects of speech retraining of adults with acquired hearing loss
- modelling belief revision in discourse for purposes of knowledge representation and reasoning

Topic – Relation gradients



Ambiguity and vagueness in lexical databases

-Ubiquitous polysemy

“In their majority, words contained in WorNet belong to more than one synsets and synsets contain words with more than one meanings, perceived as members of the specific synset under certain circumstances (most of the times defined by pragmatics).” [Source: *Poeticon 2nd year review handout*]

-Some cases of multiplicity of senses in Wordnet (*same source*):

Case: Language **changes the focus** when talking about Concepts
WordNet Example: chop, chop up: "cut into pieces" and chop, hack: "cut with a hacking tool"
Case: **Systematic polysemy**
WordNet Example: bucket, pail: "a roughly cylindrical vessel that is open at the top" and bucket, bucketful: "the quantity contained in a bucket"
Case: Language **functions metaphorically**
WordNet Example: tiger: "a fierce or audacious person" an d tiger, Panthera tigris: "large feline [...] having a tawny coat with lack stripes [...]"
Case: **Actual polysemy**
WordNet Example: seal, stamp: "a device […] used to [...] to authenticate documents" and seal: "any of numerous marine mammals that come on shore to breed [...]"

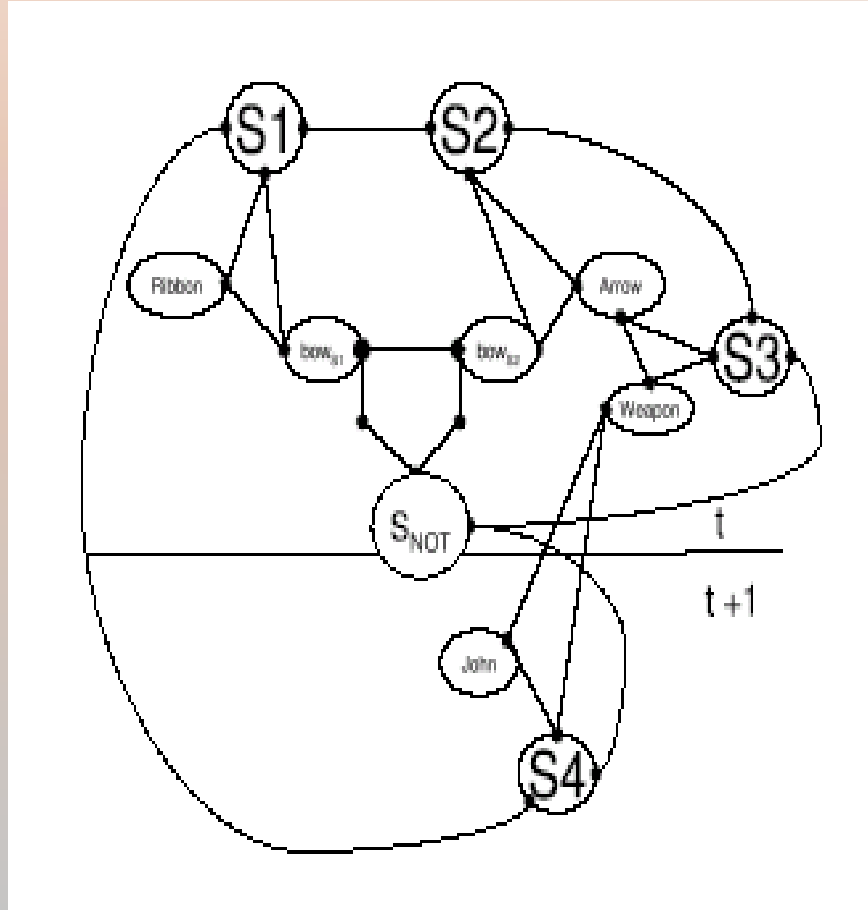
A minimal CLARNET example: the case of hononymy

Seal$_1$: Device used to authenticate document

Seal$_2$: Marine mammal that comes on shore to breed

S3: Mammals sometimes have names

S4: John met a seal named Sheila



[figure from Koutsomitopoulou 2004]

“Suidae - Hominidae”

Assume the following factoids about John in our database:

S1: Suidae are animals

S2: Pigs are Suidae

S3: Wilbur is a pig

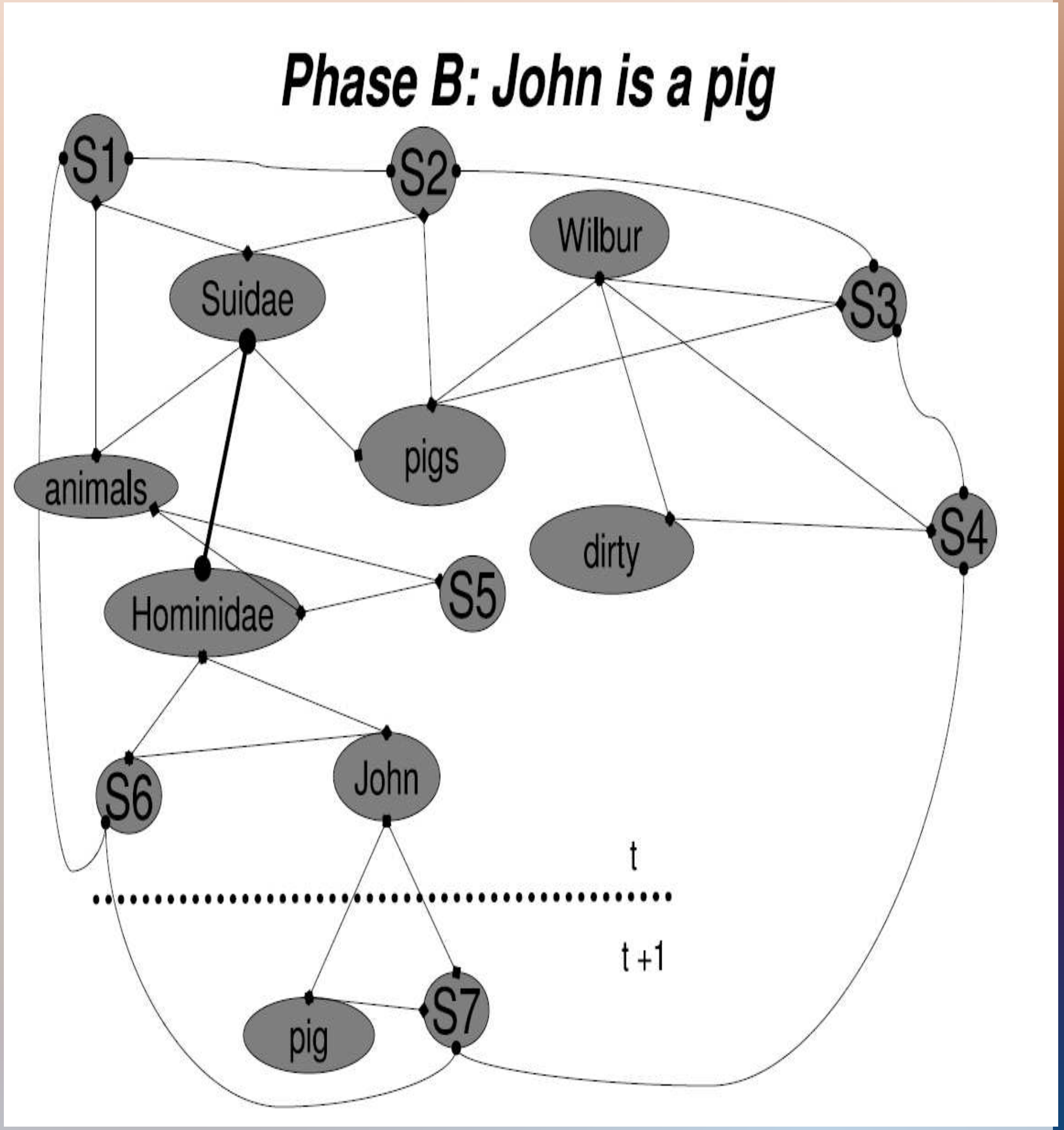
S4: Wilbur is dirty

S5: Hominidae are animals

S6: John is Hominidae

S7: John is a pig

[figure from Koutsomitopoulou 2004]



Oscillations and Stabilization during learning

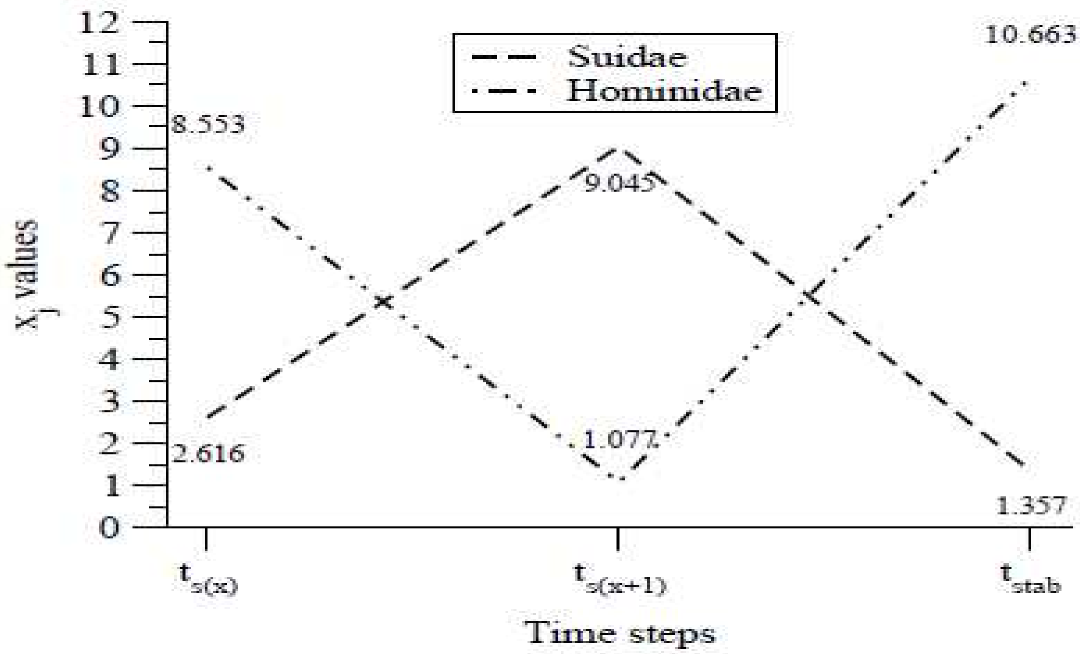


Figure 5.8: LTM effects

LTM effects

-Values of x_j when z_{ij} (LTM) is computed can be traced in order to show the prevailing pattern of neuronal activation when the network attempts to resolve the ambiguity

-Upon presentation of phasic input we observe rebound phenomena similar to those reported as *McCollough effects* when modelling vision

-Polarization and crossover of final x_j values are clearly observed indicating that the network has stabilized at a state of context-bound disambiguation

“Crossroads”

Assuming the following factoids about John in our database:

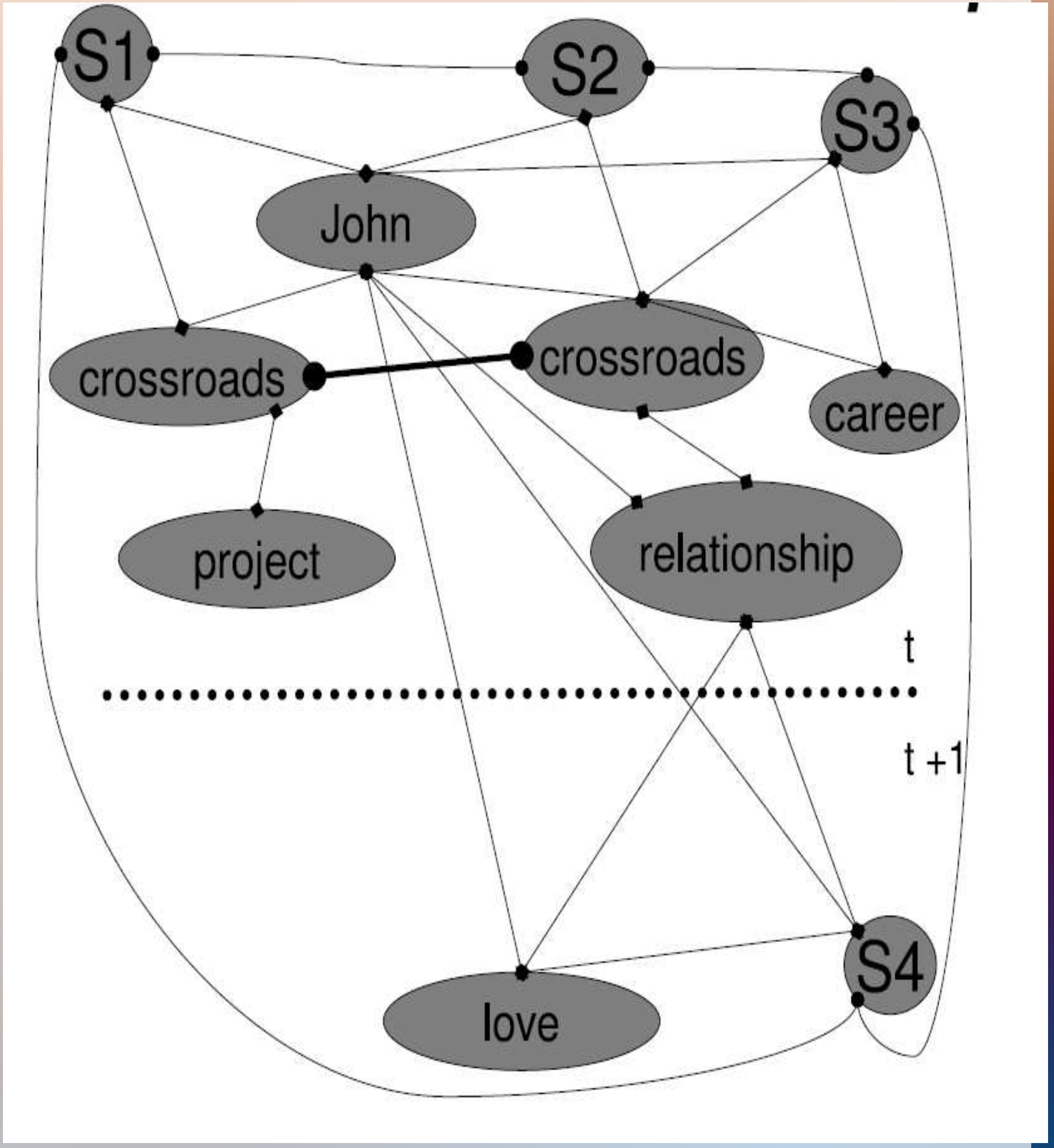
S1: John is at a crossroads in this project

S2: John is at a crossroads in his relationship

S3: John is at a crossroads in his career

S4: John is in love

[figure from Koutsomitopoulou 2004]



Disambiguation above threshold

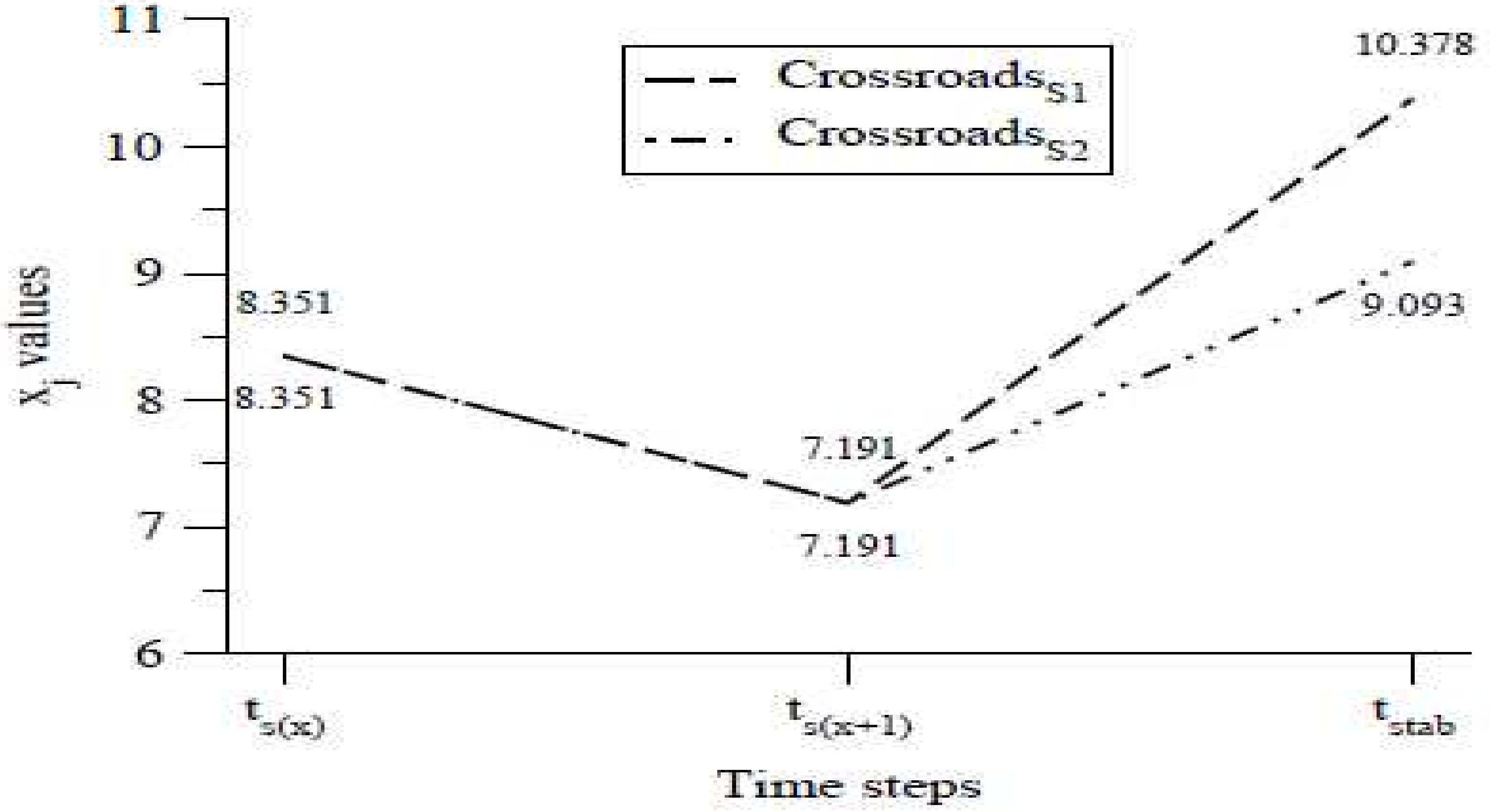


Figure 5.9: STM effects

STM effects

- There is an observed boost but no observed polarity and crossover of the final x_j values, unlike what is observed when LTM is calculated
-As long as activation is beyond threshold the network can converge into a solution
-Better x_j discrimination is obtained when LTM is computed since STM activation entails no inhibition is involved in the learning of the antagonistic dipole

Resonance and context: a review of dynamic semantics

-there is no such thing as isolating static meaning

-even when we capture patterns of activation that indicate the emergent meaning at time X and context {a,b} we fundamentally restrict -in time and space- a naturally dynamic, ever-changing, and inherently ambiguous cognitive event

-meaning is in the eye of the beholder

Further applications/extensions of the model

- modelling for the extraction of lexical relationships and for purposes of mining databases/taxonomies
- modelling for pattern recognition in sentiment detection, topic/text classification, authorship validation
- modelling speech and language processing in the context of various communication disorders (Parkinson, King-Kopetzky Syndrome, aphasia, etc.)

Epilogue:
The plausibility of intelligent machines

-Any type of artifacts are (naturally) missing: autonomy, free will and a biology

-When the problem is reduced to a mathematical system we lose crucial details of the problem that are parts of the solution

-Therefore, we can only *emulate* natural intelligence, although some emulations are better than others

-*Adaptive Resonance* goes a long way to define natural intelligence as expressed in the human cognitive system and so it's a promising step forward in terms of computational modelling of intelligent processes